



# Entropic Control Improvisation for Prediction, Inference, and Testing

Marcell Vazquez-Chanlatte Sebastian Junges Daniel J. Fremont Sanjit A. Seshia



CAV 20'



SGs preprint.

## Entropic Control Improvisation

Given a dynamics model and horizon  $T$ , find a policy that satisfies:

**Hard Constraint:**  $\Pr(\xi \in \psi) \geq 1$

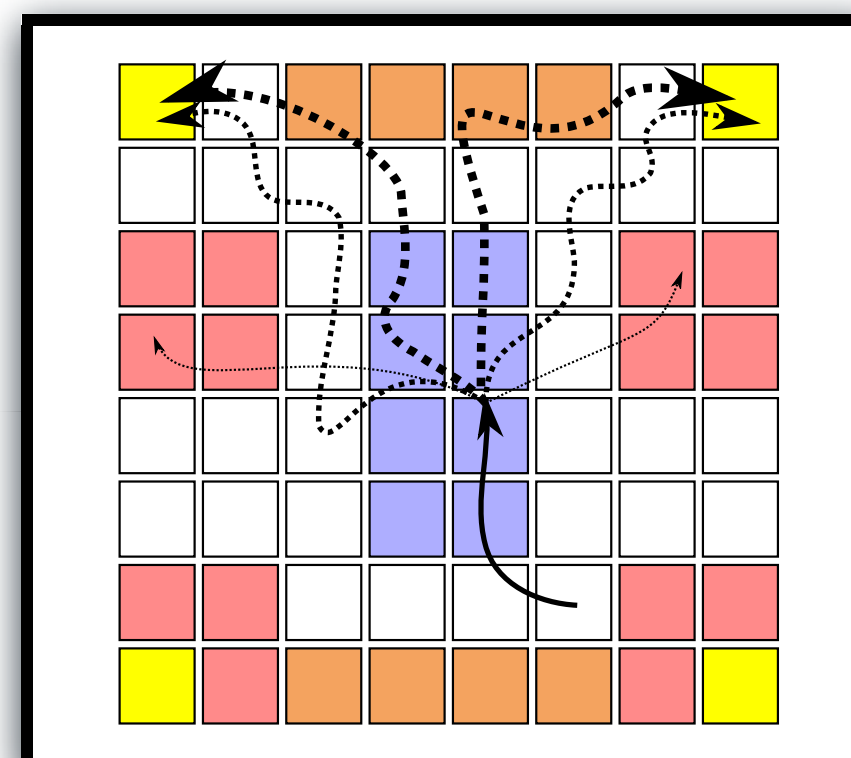
**Soft Constraint:**  $\Pr(\xi \in \varphi) \geq \mathbf{p}$

**Causal Entropy Constraint:**  $H(\mathcal{A}_{1:T} \parallel \mathcal{S}_{1:T}) \geq \mathbf{h}$

1. Causal entropy (**randomness**) constraint ensures minimal bias.
2. Natural trade off between performance  $\mathbf{p}$  and randomness  $\mathbf{h}$ .

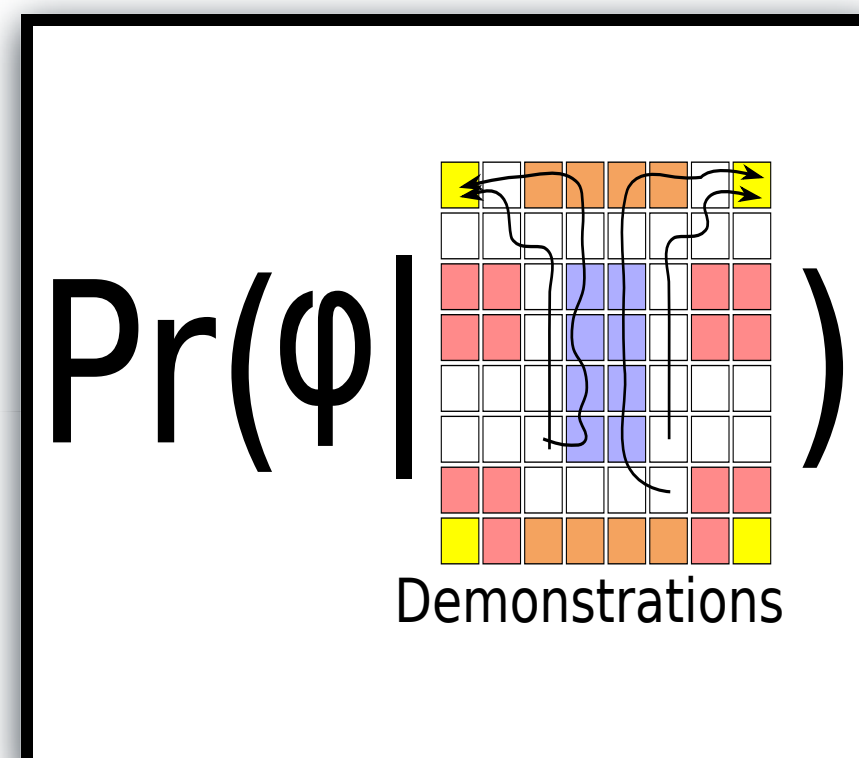
## Applications

### Prediction



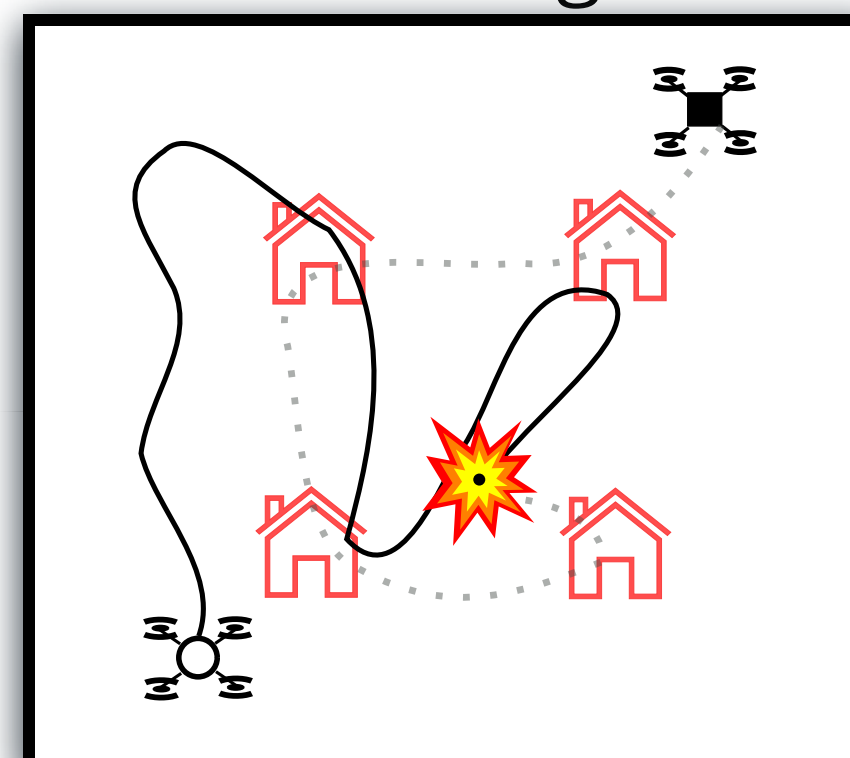
Given  $\varphi$ , predict agents next actions.

### Inference



Given demonstrations, predict  $\varphi$ .

### Testing



Declaratively specify environment for testing.

In above settings, a biased policy is **undesirable**.

## Contributions

1. Algorithm for learning temporal constraints from **unlabeled** demonstrations in Markov Decision Processes (CAV 20').
2. Symbolic approach for representing MDPs and Stochastic Games as **Binary Decision Diagrams** (CAV 20').
3. Improvisation in stochastic games which support arbitrary **combinations** of probabilistic and adversarial uncertainty (In submission).

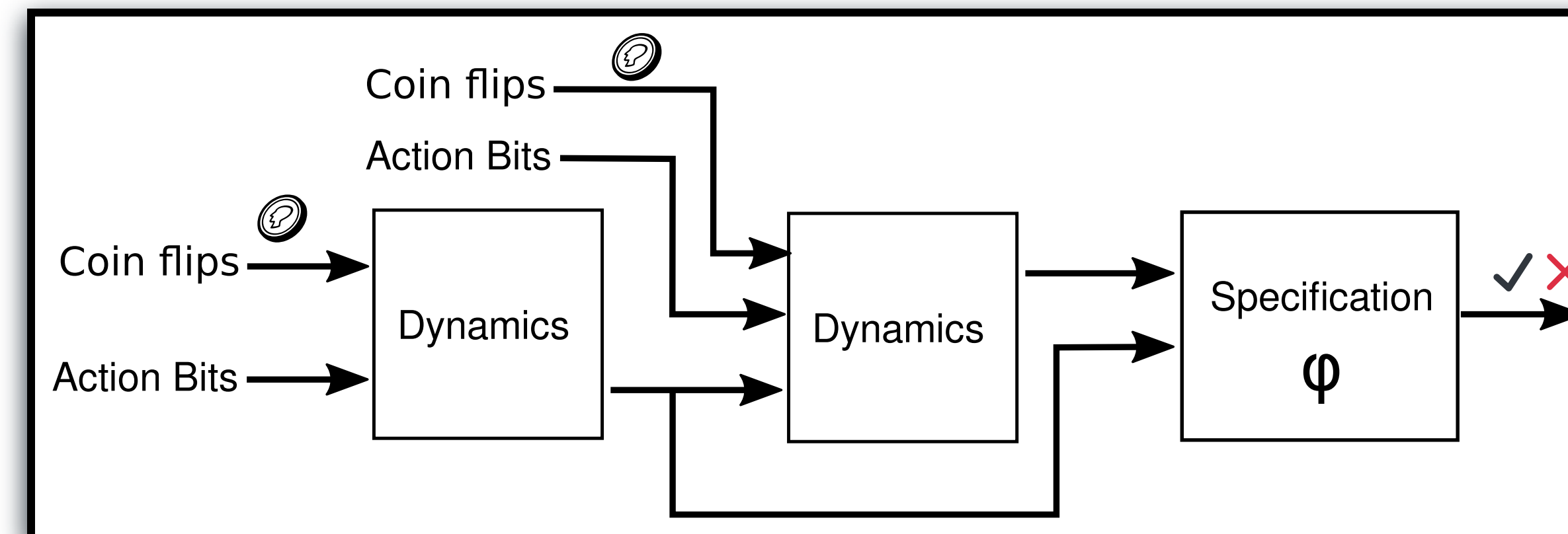
## Improv in MDPs (CAV 20')

**Key Observation:** Can think of soft constraint as binary reward.

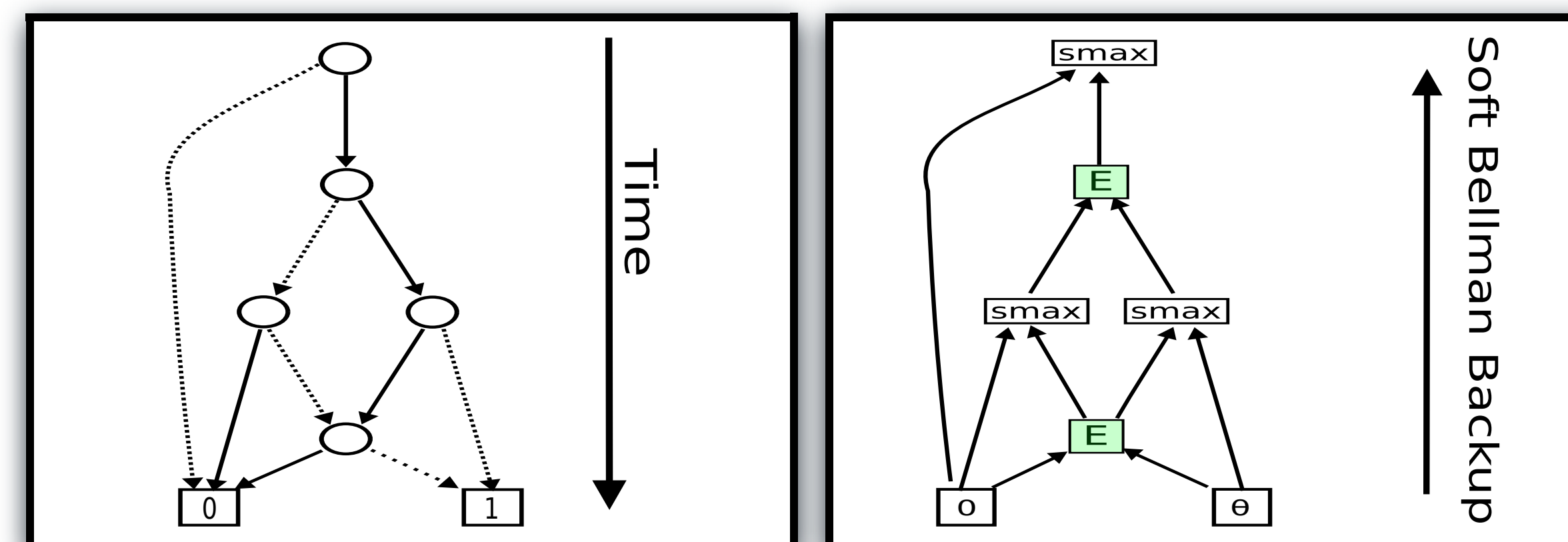
$$r_\lambda(\xi) \triangleq \lambda \cdot 1[\xi \in \varphi]$$

- By adding history to state space, can reduce to Maximum Causal Entropy Inverse Reinforcement Learning.
- **Problem:** Potential combinatorial explosion.
- **Solution:** Encode MDP as a Binary Decision Diagram.

1. Write the **composition** of the dynamics and property as a circuit with access to biased coins.



2. Can represent MDP with a Binary Decision Diagram:



**Conservative size bound:**

$$O(|\text{horizon}| \cdot |S/\varphi| \cdot |\text{Actions}| \log(|\text{Actions}|))$$

3. We show you can efficiently compute maximum causal entropy policy on compressed MDP.

**Application:** Used to learn temporal logic constraint from **unlabeled** demonstrations, e.g.,

$\varphi$  = "Avoid Lava, eventually recharge, and don't recharge while wet."

## Improv in Stochastic Games (In Submission)

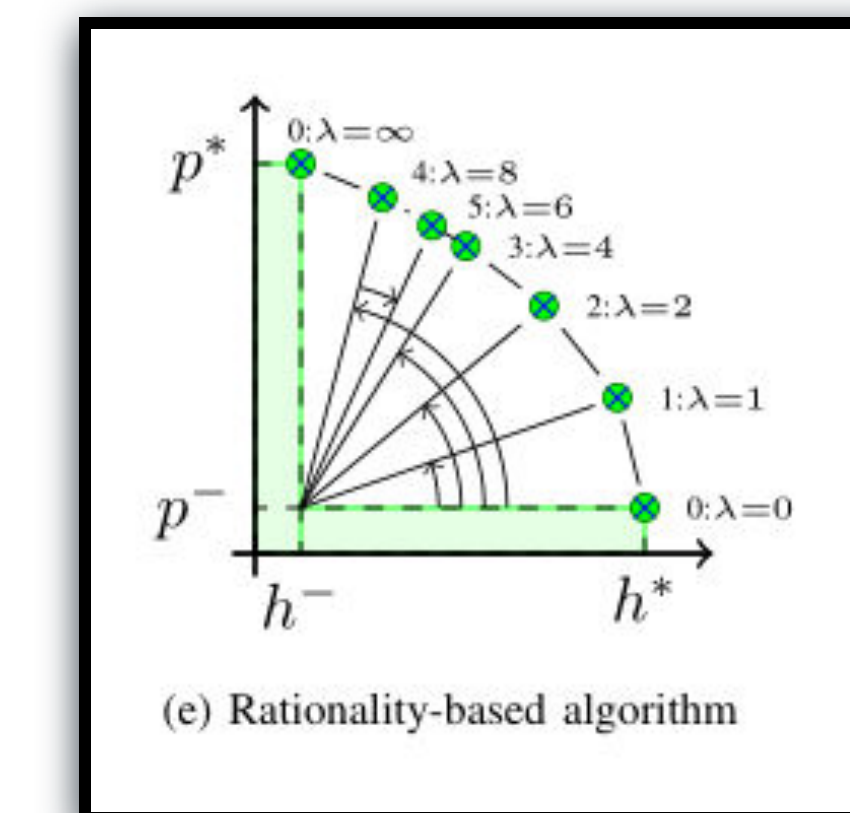
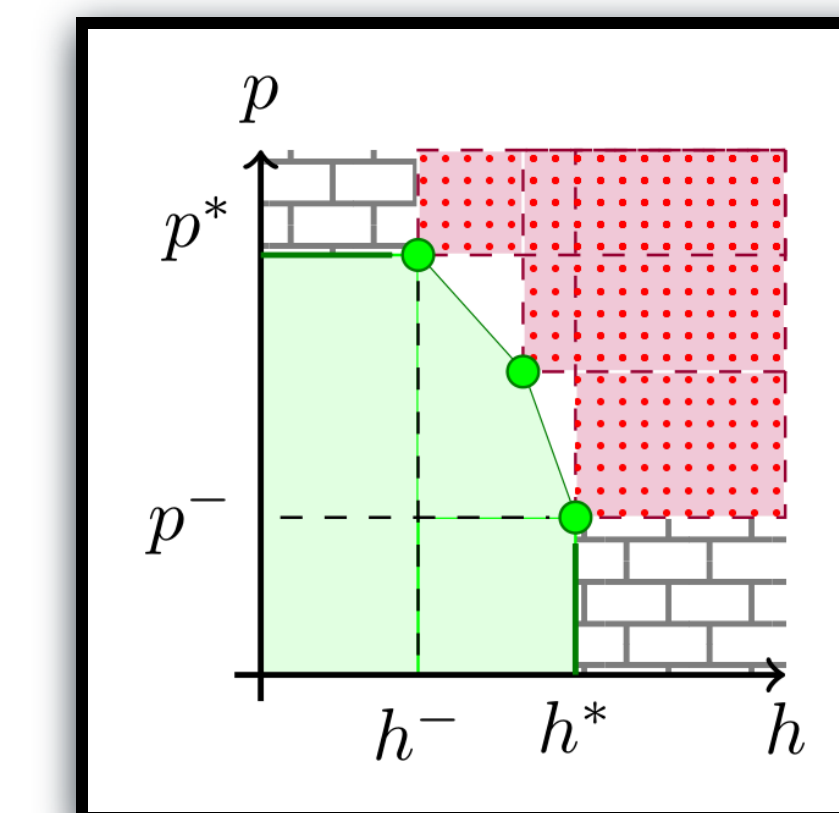
**Motivation:** Often want to handle combinations of probabilistic and adversarial uncertainty, i.e., Interval MDPs, 2 player MDPs, and model compression.

**Q:** Is efficient improvisation synthesis possible?

**A:** Yes! By **recursive entropy matching**.

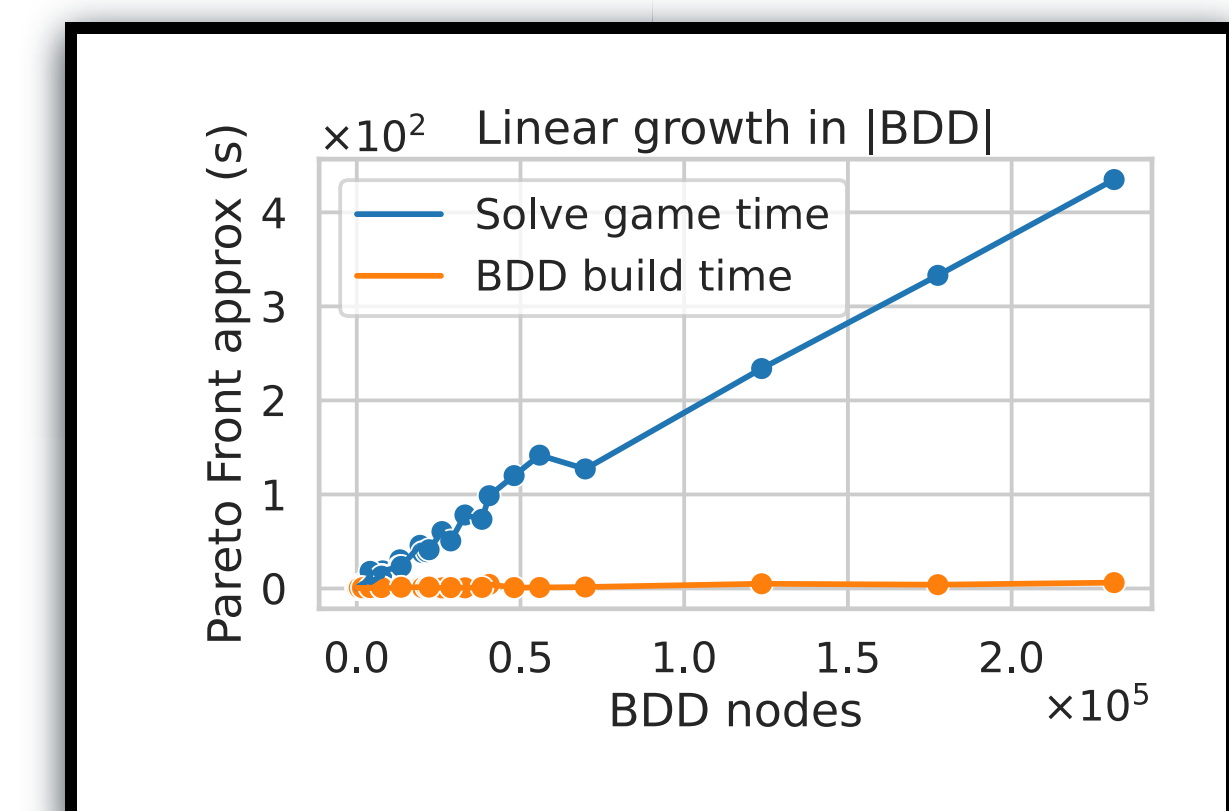
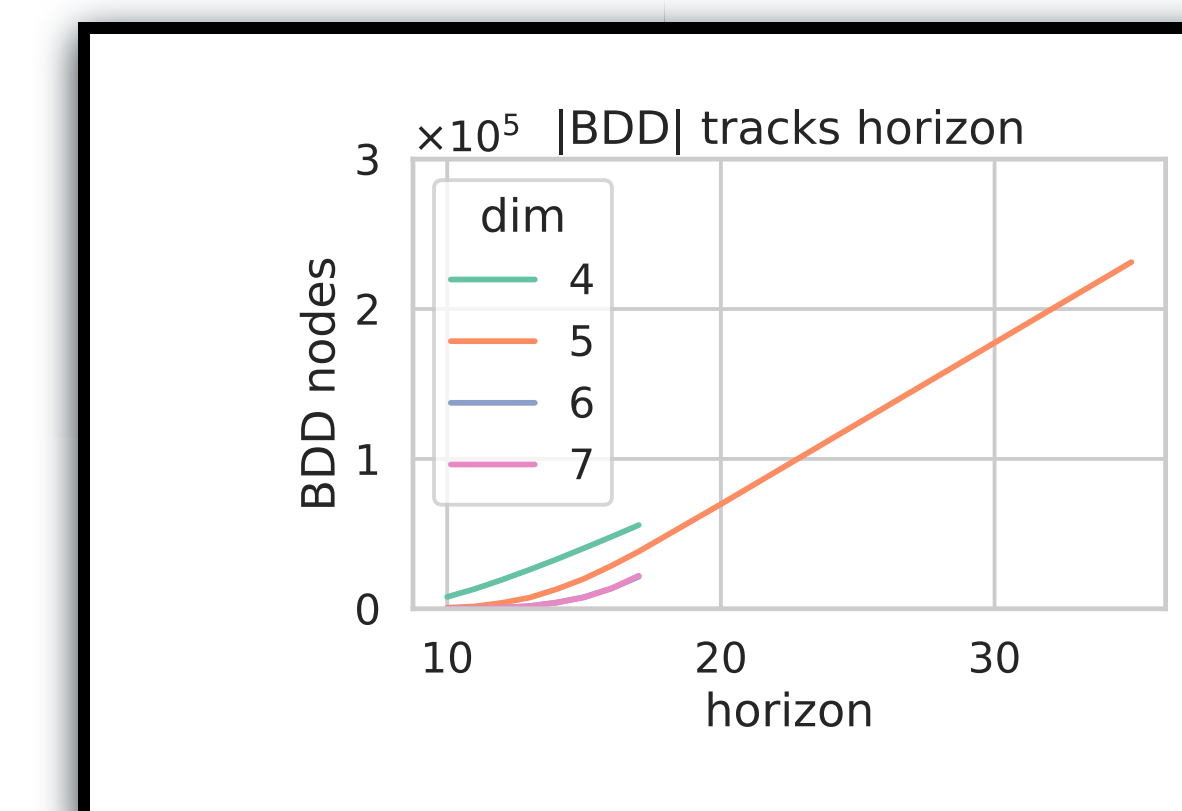
Efficient via dynamic programming from leafs of BDD.

1. Assume min entropy .
2. Run MDP to find optimal  $\mathbf{h}$ .
3. Plan to match  $\mathbf{h}$ .
4. Approximate Pareto Front.



(e) Rationality-based algorithm

1. Pareto Front allows for re-planning locally.
2. Resulting algorithm is efficient in practice.



## Future Work

1. Sampling based algorithms.
2. POMDPs.
3. Subset queries.
4. Dynamic Scenic Constraints.